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Investigations of Linear Classifiers Applied to Uncooled Infrared Imaging Face Recognition

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Abstract - **Infrared imaging devices offer the main advantage of being robust to ambient illumination changes and recent technological advances have significantly improved the resolution of cheaper uncooled infrared (IR) versions to the point where they may become widely applicable in the IR face recognition field. This study applies two linear classification schemes; the Principal Component Analysis and the Fisherface procedure to the recognition of faces collected using an uncooled IR camera under indoor controlled conditions. Results show the selected uncooled IR camera has sufficient resolution to allow for discrimination between the subjects contained in our experimental database collected. Results show also consistent better performances for LDA than for PCA-based schemes. We also discuss the impact of the first few top eigenvectors on PCA-based classification performances**.

I. INTRODUCTION

A. Background

Face recognition has received a significant amount of attention in the recent past due to its various biometric applications. Most of the face recognition studies have dealt historically with visible imaging, while very few with infrared imaging (IR) due to the much higher cost associated with cooled IR imaging devices. However, recent technological developments have resulted in uncooled IR devices with performances approaching those of cooled devices as a fraction of the cost. As a result, more attention is starting to be shown to IR face recognition applications. A few applications have been reported in the literature in the recent past [1-4,9]. Pereira investigated the application of uncooled IR imaging for face recognition using a small uncooled IR image database collected under controlled indoor conditions [2]. Selinger and Socolinsky first reported face recognition results using a combination of visible and cooled IR images [1], and extended their work recently to combining visible and uncooled IR images [3]. In addition, Chen et al. presented results combining visible and uncooled IR imaging [4].

We considered the application of two classic and widely used classification algorithms: the Principal Component Analysis (PCA) and the Fisherface Approach and report results obtained. Our study expands the initial work of Pereira [2] to a larger database of 50 adult individuals collected under controlled indoor conditions [9]. The database includes ten head tilt and angle positions in three facial expressions (neutral expression; smiling expression; and pronouncing the vowel "u" expression) for each subject, resulting in a total of 1500 images. Each subject was seated 90 cm away from the camera, so that the face occupied most of the camera filed of view. Subjects were required to rotate their heads towards nine different pre-defined directions. Figure 1 presents the front view of the camera as if the subject looked straight ahead, and illustrates the nine directions each subject was asked to look at. An additional picture was taken by asking subjects to look at a random place within the square formed by the extreme marks. Figure 2 depicts the lateral view of the camera and its distance to the seated subject.

B. Uncooled camera selection

The IR spectrum covers from 0.7 to 1,000 μm in the electromagnetic spectrum, and the camera type was selected to be best suited to collect data around 310 K, which is the average human body temperature. This constraint resulted in the selection of the IR-160 uncooled IR camera device from Infrared Solutions, Inc., sensitive in the wavelength region from 8 μm to 14 μm (i.e., the Far IR region). The camera uses a 160×120 pixel microbolometer array to obtain video frames at a 30 frames/s that can be displayed on a video monitor or/and transmitted serially via a RS-232 link using 8 bits/pixels [5]. Images were cropped to sub-images of size 60×45 to extract face-only portions (excluding ears and hair), as shown in Figure 3.

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II. FACE RECOGNITION SCHEMES

A. Introduction

Numerous classification schemes have been reported in the face recognition literature [6]. Classical and widely used linear approaches are based on eigenface (PCA) and Fisherface (a combination of PCA and LDA) concepts and/or their variants [11]. These schemes linearly project the image information onto smaller dimensional spaces, where discrimination operations are conducted. Our study is restricted to the "closed set" implementation, which assumes that all testing trials belong to the database used to design the classification algorithm.

We implemented a cross-validation variant to estimate error rates over 900 iterations generated by randomly selecting 60% of the pictures available per class to generate the training dataset for a given iteration, while the remaining 40% was used in the associated testing phase [9]. For each iteration, PCA and Fisherface projection parameters were computed from the selected training set and used to compute the class-specific centroids characterizing each subject in the database. Next, the resulting projection parameters were applied to the associated testing sets and the distances between the projections and each class centroids computed. Final classification decisions were made for each testing image by selecting as class that closest in Euclidian norm to the projected testing image [2,9]. Finally, averaged and median error rates obtained from the 900 iterations were computed.

B. Principal Component Analysis (PCA)

The overall goal behind the PCA is to determine the least amount of components needed to measure most of the dataset variance. Such a process is implemented by computing a linear projection matrix which also reduces the dimensionality of the original problem and greatly simplifies the analysis [11]. PCA is best suited for compression applications, but has also been used with success in classification applications, even though discriminative information may be contained in low energy details which are not necessarily kept by the PCA approach. The PCA-based projection matrix W is obtained from the eigendecomposition of the training dataset total scatter matrix S defined as:

$$S = \sum_{k=1}^{N} (\underline{x}_k - \underline{m})(\underline{x}_k - \underline{m})^T ,$$

where $\underline{x}_k$ is the kth cropped image reshaped as a column vector of dimension $60\times45=2700$ in our study, N represents the number of images in the training dataset (equal to 900 in our study), and $\underline{m}$ corresponds to the training dataset sample mean. The projection matrix can be shown to correspond to the eigenvectors associated to the top K eigenvalues in magnitude, where the specific number K is user-specified, and is usually selected as to discard eigenvectors with close to zero eigenvalues. Note that the scatter matrix can be viewed as a matrix product of the type XX^T, where X is of size 2700×900, resulting in a scatter matrix of dimension 2700×2700 in our study, and a heavy computational load required for the eigendecomposition. As a result, we follow the Snapshot approach discussed earlier by Yambor [12] which takes advantages of the facts that; 1) the non-zero eigenvalues of XX^T and X^TX are the same, and 2) the eigenvectors associated with the non-zero eigenvalues of XX^T are the same as the eigenvectors of X^TX multiplied by the matrix X and normalized. Thus, the Snapshot method generates the PCA projection matrix from the eigendecomposition of a 900×900 matrix rather than the 2700×2700 covariance matrix, resulting in significant computational savings.

C. Fisherface Analysis

As discussed above, the PCA is not well matched for classification applications, as it may lead to discarding details which are contained in the eigenvectors associated with the smaller eigenvalues in magnitude. The objective of the LDA is to perform dimensionality reduction while preserving as much class discriminating information as possible [11]. The LDA approach uses between-class and within-class scatter matrices S_B and S_W which are defined on the training data as

$$S_B = \sum_{i=1}^{C} n_i (\underline{m}_i - \underline{m})(\underline{m}_i - \underline{m})^T ,$$

where C and $\underline{m}$ represent the total number of classes and the overall mean vector for the training set, while n_i and $\underline{m}_i$ represent the number of images and the class-specific mean vector for class C_i respectively, and

$$S_W = \sum_{i=1}^{C} \sum_{x\in C_i} \left(\underline{x} - \underline{m}_i\right)\left(\underline{x} - \underline{m}_i\right)^T .$$

The optimal linear projection matrix W_F can be shown to be that obtained by solving the following generalized eigenproblem:

$$S_B \underline{w} = \lambda S_W \underline{w},$$

provided the matrix S_W is not singular. However, it is to be noted that in face recognition applications the matrix S_W is usually singular, as the number of images is usually smaller than the size of the reshaped image vectors, as is the case in our study. Therefore, Belhumeur et al. proposed in the Fisherface approach to first apply PCA to project the information into a lower dimensional space so that the transformed matrix S_W is non-singular before applying the LDA step [13].

III. CLASSIFICATION RESULTS

Unless mentioned otherwise, all results presented are those obtained with the 900 iterations validation variant discussed earlier in Section II.A to minimize the potential impact due to partitioning the data between non-overlapping training and testing sets when dealing with a small number of images per class.

A. PCA-based Approaches

- Projection matrix dimension issues

First, we investigated how the number of top eigenvectors selected to define the PCA-based projection matrix defined earlier impacted the resulting error rate. Figure 4 shows a representative plot of the average error rate as a function of the top eigenvectors kept in the projection matrix which indicates no significant classification improvement by keeping above 50 eigenvectors. As a result, we implemented PCA-based classification schemes keeping all eigenvectors associated with non-zero eigenvalues, with the top 80 and the top 50 eigenvectors for comparison purposes, and computed mean and median error rates over 900 iterations. Table 1 presents mean and median error rates (expressed in %) for these three basic PCA-based schemes. Mean error rates are 20.78%, 21.26% and 22.47% respectively. Results show a slight degradation in performances by reducing the dimension of the projection matrix.

- Top eigenvector influence issues

Pereira showed in an earlier study that on a small database consisting of the first 14 subjects included in the current database, classification performances improved by removing the top three eigenvectors from the PCA-based projection matrix [2]. Such a procedure is commonly used for visible imaging data, as the first top few eigenvectors are primarily associated with lighting variations, and recognition rates are improved by removing them [8]. However, such a result was not expected in IR imaging where lighting variations is not expected to be an issue. Therefore, we extended this earlier study to our 50 subject database to investigate whether these findings were still present in a larger database. Average and median error rates obtained with 200 iterations by keeping 50 eigenvectors to define the projection matrix are included in Tables 2 and 3. Results show that the trend noted in the earlier small database study does not extend when the database size increases [2,9]. Further details are available in Lee [9]. Overall median and mean error rates obtained for 900 iterations using the 50 subject database is also included in Table 1, where PCA*N*W*B* refers to the PCA algorithm implemented with *N* eigenvectors after removing the top *B* eigenvectors first.

B. Fisherface Approach

Tables 1 to 3 also include the overall mean and median error rates obtained for the Fisherface implementation and show the significant better mean and median performances obtained with this scheme [8].

IV. CONCLUSIONS

This study investigated face recognition using an uncooled infrared camera with a database of fifty adult subjects collected under controlled indoor conditions. We focused on two linear schemes; PCA and the Fisherface approach which is a combination of PCA and LDA. Results show that uncooled infrared imaging is a viable candidate for face recognition applications with an average classification performance for the Fisherface approach equal to 94.58%. Results also show much lower performances for PCA-based schemes with the best average classification performance equal to 89.22% for all variant considered in the study. We also extended an earlier investigation regarding the impact of the first few top eigenvectors on resulting PCA-based classification algorithms performances. Results show that performance degradation is observed by removing the first few top eigenvectors contribution as the database size increases. Both classification approaches have limitations as they are based on linear projections. Extensions to nonlinear kernel-based classification algorithms, currently under study, show that additional classification performance improvements are observed when applying the Generalized Discriminant Analysis Approach [10].

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Scheme Implemented	Mean Error Rate (%)	Median Error Rate (%)
PCA-all	20.78	16.96
PCAW1	24.54	21.45
PCAW2	24.99	24.21
PCAW3	27.56	26.63
PCA80	21.26	17.38
PCA80W1	25.06	22.56
PCA80W2	25.61	24.89
PCA80W3	28.19	27.24
PCA50	22.47	18.84
PCA50W1	26.61	24.87
PCA50W2	27.35	27.07
PCA50W3	29.97	29.46
Fisherface	5.42	4.07

Table 1. Mean & median error rates (%); 50 classes; 900 iterations. PCA*N*W*B* refers to the PCA algorithm implemented with *N* eigenvectors after removing the top *B* eigenvectors first.

No of classes	Number of (eigenv. kept, top eigenv, omitted)						Fisherface
	(50,0)	(50,1)	(50,2)	(50,3)	(50,4)	(50,5)	
14	12.67	11.13	12.15	5.21	7.29	12.50	0.10
15	12.04	8.38	7.21	3.33	5.88	8.29	0.08
16	9.25	6.83	8.58	10.35	7.00	9.00	0.04
17	4.17	5.54	6.50	11.54	6.71	11.88	0.00
18	4.63	7.54	9.71	13.90	9.17	12.15	0.02
19	5.58	5.75	7.83	15.08	7.13	12.42	0.04
20	5.23	6.71	10.19	14.98	10.69	12.42	0.06
25	6.04	11.88	12.00	15.88	17.33	14.79	0.33
30	9.73	15.42	17.73	20.90	18.27	18.73	1.40
35	14.29	16.5	22.54	27.54	20.97	25.71	2.04
40	16.06	19.17	25.33	29.52	24.85	27.48	2.71
45	18.13	25.17	27.42	29.50	27.54	29.92	3.79
50	19.25	26.66	27.51	30.02	28.75	32.57	4.04

Table 2. Median error rate (%) as a function of the number of classes; 200 iterations.

No of classes	Number of (eigenv. kept, top eigenv, omitted)						Fisherface
	(50,0)	(50,1)	(50,2)	(50,3)	(50,4)	(50,5)	
14	17.88	13.19	12.31	8.51	10.03	14.31	0.62
15	16.38	11.30	11.04	8.24	9.08	12.13	0.42
16	15.61	12.29	11.36	11.93	10.41	11.08	0.34
17	14.87	12.45	12.25	16.23	11.64	12.29	0.29
18	14.22	13.13	12.71	17.44	12.94	13.56	0.58
19	13.95	12.77	12.02	16.52	12.78	14.15	0.67
20	13.05	13.34	13.08	18.21	13.79	14.99	0.76
25	12.90	16.12	16.56	20.20	16.10	17.26	1.96
30	14.76	19.40	20.68	23.78	19.13	21.59	2.60
35	17.35	22.19	23.85	28.48	22.62	25.21	3.60
40	19.25	23.78	26.01	29.15	24.86	27.58	4.08
45	21.48	25.97	27.31	29.44	27.11	30.96	4.78
50	22.39	26.66	27.51	30.02	28.77	32.57	5.39

Table 3. Mean error rate (%) as a function of the number of classes; 200 iterations.

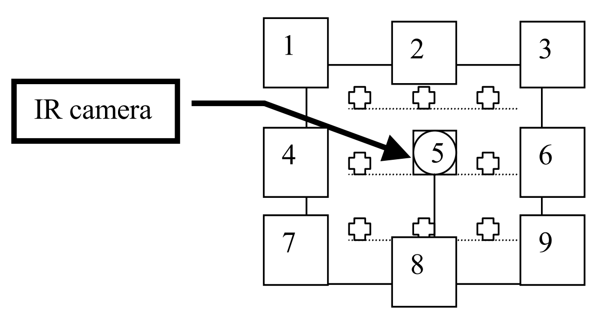

Figure 1. Front view IR camera set-up [2].

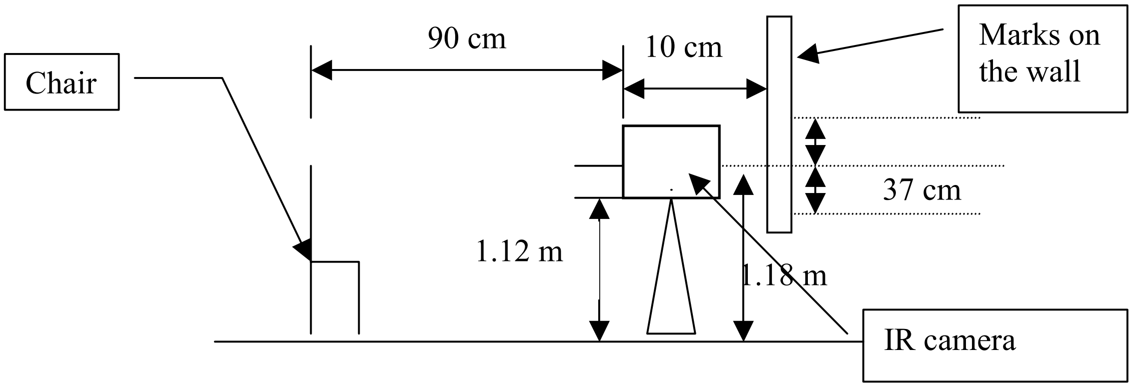

Figure 2. Lateral view IR camera setup.

Figure 3. Cropped face; from [2].

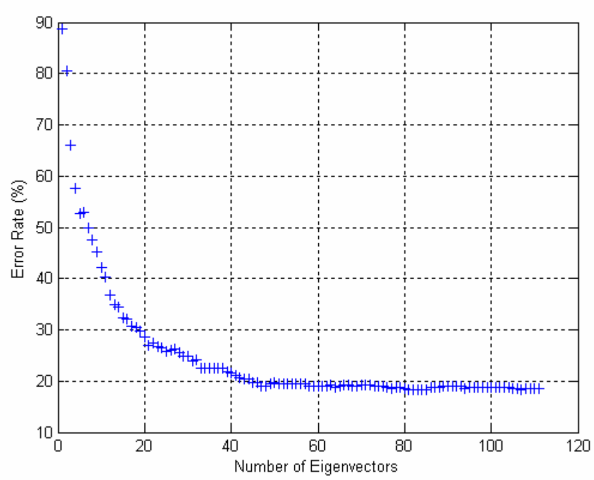

Figure 4. Mean error rate (%) vs. number of eigenvectors used in PCA Classification; one iteration.